Path Planning Analysis of Mobile Robot with Improved Ant Colony Algorithm

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***Abstract*—Aiming at the problems of poor convergence and local optimization in path planning using the basic ant colony algorithm, this paper studies an improved ant colony algorithm to enhance the effect of mobile robot path planning. Firstly, the state transition probability of the ant colony algorithm is modified, and the influence of the angle on node selection is increased by adding a new angle index heuristic function. Then, the sorting and elite ant colony algorithm strategies are fused to research a path length difference pheromone update method, improving the efficiency of the ant colony algorithm in planning the optimal path. Finally, through a comparison with the basic ant colony algorithm simulation on MATLAB, the feasibility and effectiveness of the improved ant colony algorithm are verified.**

***Index Terms*—Mobile robot, Path planning, Ant colony algorithm, Heuristic function, Pheromone update method**

I. INTRODUCTION

Intelligent robots, as products of modern science and technology integrating modern control theory, mechanical and electronic engineering, computer engineering, and artificial intelligence, have been widely used in manufacturing and service industries [1]. Path planning is one of the necessary preconditions for mobile robots, an important branch of robots, to realize autonomous movement. Path planning refers to a path that the robot can follow to avoid obstacles in an open environment and safely drive to the target point according to certain evaluation criteria (such as the shortest path length, shortest planning time, or comprehensive consideration) [2]. According to the intelligence of its algorithm, path planning can be divided into traditional path planning algorithms and intelligent path planning algorithms. Visibility graphs [3], A* algorithm [4], and artificial potential field methods [5] are all traditional path planning algorithms. However, with the increase in the complexity of robot working environments, traditional path-planning algorithms show certain deficiencies in environmental adaptability. The emergence of intelligent path planning algorithms such as neural network algorithms [6], genetic algorithms [7], and ant colony algorithms [8] further broadens the scope of application of robot path planning.

The ant colony algorithm is a swarm search intelligent path planning algorithm, which has been widely used in the global path planning of mobile robots due to its strong robustness and good parallelism. However, in the process of path planning, the ant colony algorithm also has some shortcomings, such as local optimization and long calculation time, so many scholars have improved it [9], [10]. Jiang et al. [11] distinguished the initial pheromone concentration by establishing a favorable position between the starting point and the target point to improve the search efficiency of the ant colony algorithm in the early stage. The structure of the ant colony algorithm was improved by adopting the pseudo-random state transition probability controlled by dynamic parameters and the principle of updating high-quality ant pheromone, together with the method of adaptive volatilization coefficient, which plays a good effect on the global optimality of the algorithm. Tu et al. [12] carried out improvements to the basic ant colony algorithm from two aspects to improve the optimal path efficiency of ant searching. Firstly, a directional sandwich inspired function was established to make ants selectively choose nodes. Then, a complex distance inspired function was established to reduce the operational link of the square root and reduce the computational effort of the algorithm. Xu et al. [13] proposed an adaptive step-size ant colony algorithm to reduce unnecessary inflection points in single-step planning routes, improve the smoothness of route planning, and reduce the planned route length. At the same time, to improve the convergence of the algorithm, a point with a short distance from the starting point and the target point was selected as a feasible node, and a new distance heuristic function was established. Wan and Peng [14] aimed at improving the traditional ant colony algorithm, which uses the same method for each iteration, leading to the ant search falling into the local optimal update mode. An unequal update mode for high-quality ants and inferior ants was studied to improve the optimization efficiency of ants. Then, the method of simplifying operators was adopted to delete unnecessary path nodes and reduce the planned path length. Chen and Han [15] adopted a pseudo-random selection ratio of state transition probability which varies with the number of iterations and a distance heuristic function which varies with the number of iterations nested in the iterative process. This accelerates the convergence speed of the algorithm and improves the algorithm's global performance.

To make the ant colony algorithm perform better in route planning, this paper optimizes the ant colony algorithm in route planning and convergence by adding an included angle heuristic function to judge the included angle of nodes, modifying the state transition probability of the ant colony algorithm, not updating the ant pheromone on the poor path, and updating the ant on the better path with differentiated

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pheromone.

II. Environment Modeling

In the grid method, the environment model is divided into a series of grids with the same size, i.e., white feasible grids and black infeasible grids, according to whether the grids are feasible or not. Because of its characteristics of easy implementation and good intuition, the grid method has been widely used in robot environment modeling. Therefore, the grid method is selected to build a two-dimensional space environment model for mobile robots, as shown in Fig. 1 [16].

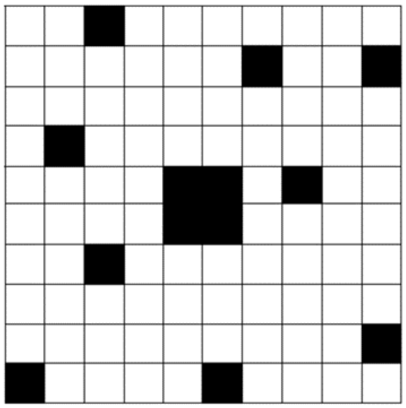

Fig. 1. Grid model.

III. Classical Ant Colony Algorithm

In the basic ant colony algorithm, the choice of path mainly depends on the pheromone concentration on the path and the heuristic of nodes, while the mathematical model of the ant colony algorithm can be composed of two parts: state transition probability and pheromone update.

The state transition probability of the ant colony algorithm means that ants choose feasible nodes according to the probability value of a certain node. Generally, the roulette method is used to calculate the probability from the current node to the next node, so the probability P_{ij}^k of feasible node j is:

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}\cdot\eta_{ij}^{\beta}}{\sum\limits_{s\in \text{allowed}k} \tau is^{\alpha}\cdot\eta_{is}^{\beta}}, & j \in \text{allowed}_k \\ 0, & j \in \text{allowed}_k \end{cases} \tag{1}$$

$$\eta_{ij} = \frac{1}{d_{jE}} \tag{2}$$

where,
τ_{ij} = the pheromone concentration;
η_{ij} = the distance heuristic function;
d_{ij} = the Euclidean distance between feasible node j and target point E;
α = the pheromone concentration factor;
β = the heuristic function factor;
allowed_k = the next feasible node set of ant k.

The pheromone update of the ant colony algorithm is to update the pheromone concentration on the path of ants reaching the target point after each iteration and achieve a certain balance of the pheromone concentration on the path by releasing a part of the pheromone and volatilizing a part of the pheromone. The algorithm pheromone update mode is as follows:

$$\tau_{ij}(t) = (1-\rho)\cdot\tau_{ij}(t-1) + \Delta\tau_{ij}(t) \tag{3}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^k(t) \tag{4}$$

where,
$\rho \in (0,1)$ = the pheromone volatilization coefficient;
$(1-\rho)$ = the pheromone residual coefficient;
$\Delta\tau_{ij}$ = the pheromone increment on the path from node i to feasible node j;
$\Delta\tau_{ij}^k$ = the pheromone left by the k-th ant on the path ij.

$$\Delta\tau_{ij}^k(t) = \begin{cases} \frac{Q}{L_k}, & \text{Path(i,j) for ant k} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where,
Q = the pheromone enhancement coefficient;
L_k = the path length searched by the k-th ant.

IV. Improved Ant Colony Algorithm

In the path search of the classical ant colony algorithm, the result mainly depends on the pheromone concentration in the path and the heuristic interaction of the nodes. When the pheromone concentrations in path planning have little difference, the degree of perspective of ants in path search is larger because of the heuristic of the node. On the contrary, the positive feedback of pheromone is strong, and the ants will tend to have more pheromone concentration on the path when searching for the next path. Such a path-searching method, which is susceptible to single factors and is undifferentiated, cannot guarantee the efficiency of path planning. Therefore, to improve the performance of the ant colony algorithm, the following improvements are made to the classical ant colony algorithm in this paper.

A. Establishing an included angle heuristic function

The selection of nodes is determined according to pheromone concentration and heuristic function. When there is little difference in pheromone concentration, the heuristic function is embodied. However, the basic ant colony algorithm is limited by a single distance heuristic function, which selects feasible nodes by the distance between feasible nodes and target points. Although using the distance heuristic function of the target point can speed up the ants to find the path, it cannot guarantee whether the found path will fall into the local optimum. According to Fig. 2, by observing the included angle between the feasible node j on routes 1 and 2 and the current node i and the target node E, it is found that the larger the angle θ_{ij}, the closer the feasible node is to the target point, which means that the probability of finding the optimal path increases. Therefore, a heuristic function factor about the angle between nodes is established to increase the probability of ants choosing the optimal path. Besides, to enhance the proportion of the heuristic function of node angle in node heuristic, a dynamic e is selected to increase the heuristic function of node angle. The newly established included angle heuristic function ϕ_{ij} is:

$$\phi_{ij} = e^{\theta_{ij}/\pi} \tag{6}$$

Then the distance heuristic function for ants to select the next feasible node is as follows:

$$\eta_{ij} = \frac{\phi_{ij}^{\gamma}}{d_{ij}} \tag{7}$$

where,
ϕ_{ij} = the heuristic function of the included angle index;
γ = the heuristic function factor.

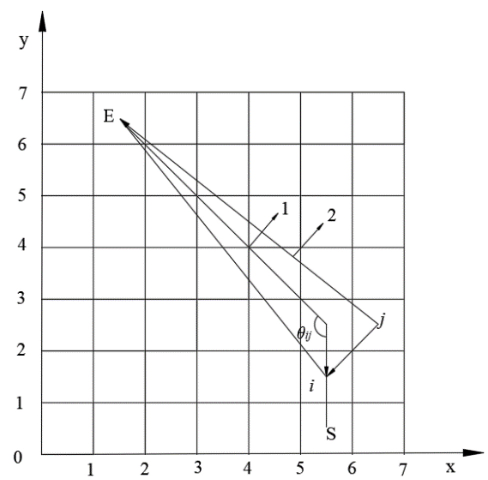

Fig. 2. Included angle of nodes.

B. Differentiated pheromone updating method

In the process of ants searching, the pheromone concentration on the route will play an important role in planning the route, while the pheromone update of the basic ant colony algorithm is to update all ants arriving at the target point, which is not only computationally intensive but also susceptible to the pheromone released by poor ants, which interferes with the probability of ants choosing the optimal route, and the convergence of the algorithm is not too fast. To improve the efficiency of the algorithm to search for the optimal path, in this paper, based on the idea of ranking ant colony algorithm, a pheromone update method based on part of the high-quality path is proposed. By abandoning ants whose path length is longer than the average path length in each iteration, it can avoid taking only the first w ants based on the sorting strategy, but the effect of path planning of the algorithm will be affected when the $(w+1)$-th ant and the w-th ant have the same path length and are not updated by pheromones. Although only updating the pheromone concentration on a part of the optimal solution path can reduce the influence of the pheromone concentration on a poor path, the degree of differentiation of the pheromone concentration on the path of the ants in the area of the better path is still not large according to the basic ant colony algorithm pheromone updating method. A pheromone update mode with different path lengths is formed, which makes ants tend to choose the best path and, at the same time, keeps the attraction of the better path to the next path search, which improves the efficiency of searching for the global optimal path when the ants search for the path. Differentiated pheromones are updated as follows:

$$\tau_{ij}(t) = (1-\rho)\cdot\tau_{ij}(t-1) + \Delta^{*}\tau_{ij}(t) \tag{8}$$

$$\Delta^{*}\tau_{ij}(t) = \sum_{k=1}^{m}\Delta^{*}\tau_{ij}^{k}(t) \tag{9}$$

$$\Delta^{*}\tau_{ij}^{k}(t) = \begin{cases}\varepsilon_h\frac{Q}{L_k}, & Path(i,j)\\ 0, & \text{otherwise}\end{cases} \tag{10}$$

where,
$\Delta^{*}\tau_{ij}$ = the pheromone increment on the optimal path;
$\Delta^{*}\tau_{ij}^{k}$ = the pheromone increment of the k-th ant on the optimal path.
Coefficient ε is expressed as

$$\varepsilon = \begin{cases}1+\frac{L_{\text{max}}}{L_{\text{min}}}, & L_k = L_{\text{min}}\\ 1-\frac{L_k}{L_{\text{ave}}}, & L_{\text{min}} < L_k <= L_{\text{ave}}\\ 0, & L_K > L_{\text{ave}}\end{cases} \tag{11}$$

where,
ε = the pheromone differentiation coefficient;
L_{min} = the minimum path length of this cycle;
L_{ave} = the average path length of ants reaching the target point.

C. Flow of improved ant colony algorithm

Environment modeling. The grid method is used to model the working environment of the mobile robot. Parameter initialization. The starting point and the target point of the path planning are set, and the parameters such as the pheromone concentration, the heuristic function factor, and the pheromone volatilization coefficient of the ant colony algorithm are initialized. Selection of feasible nodes. Ants select nodes according to the transfer formula (8) of improved ant colony algorithm state. Judging whether the target point is reached. When the ant does not travel to the target point, it continues to search the path according to process 3 until it reaches the target point; otherwise, it proceeds to the next step. Pheromone upgrade. The ants that have searched the target point are updated according to the differentiated pheromone update mode. Judging whether the maximum iteration times are reached. When the current iteration number does not reach the maximum iteration number, the ant continues the path search according to process 2; otherwise, the loop operation is ended to output the optimal path length.

V. Experimental Simulation and Analysis

To verify the performance of the improved ant colony algorithm, two environment models with different complexity are set up in this paper, which are 20×20 environment model and 30×30 environment model. The basic ant colony algorithm and the improved ant colony algorithm for parameter optimization are simulated 20 times each on the MATLAB simulation platform, and the algorithm performance is compared from five aspects of optimal path length, optimal iteration times, average path length, average iteration times, and average calculation time. The parameter settings of basic and improved ant colony algorithms are shown in Table I.

TABLE I
Parameter setting of basic and improved ant colony algorithm.

Ant colony algorithm	Pheromone factor	Heuristic function factor	Pheromone intensity	Pheromone volatility coefficient	Ant population	Max iterations
Basic ant colony algorithm	1.5	8	10	0.2	70	100
Improved ant colony algorithm	1	5	5	0.7	50	100

A. 20×20 environmental model

In terms of the performance of the improved ant colony algorithm, firstly, the improved ant colony algorithm is verified under a simple 20×20 environment model. After running both the basic and the improved ant colony algorithm for 20 times, it is found that both the basic ant colony algorithm and the improved ant colony algorithm can search the optimal planning route, as shown in Fig. 3, and their corresponding optimal convergence curves are shown in Fig. 4 and Fig. 5, respectively.

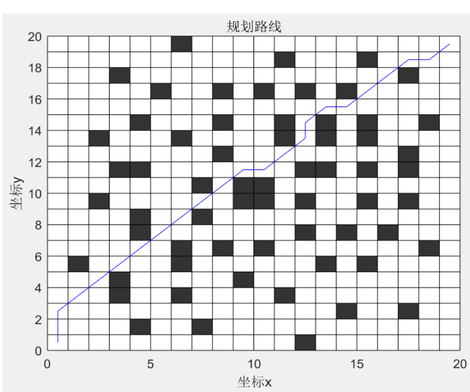

Fig. 3. Optimal route planning for two algorithms.

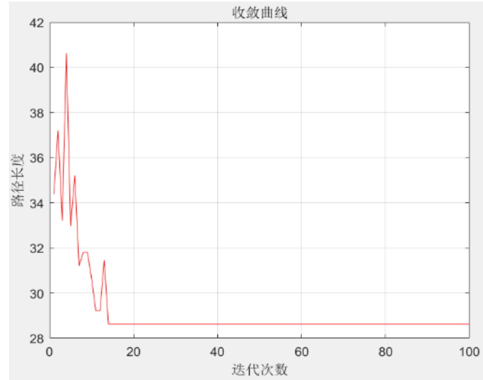

Fig. 4. Convergence curve of basic ant colony algorithm.

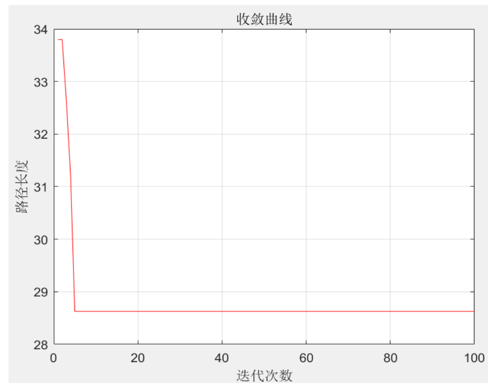

Fig. 5. Convergence curve of improved ant colony algorithm.

The simulation results of the basic and the improved ant colony algorithm for 20 times are statistically compared from the optimal planned route length, optimal iteration times, average path planning length, horizontal iteration times, and average calculation time, as shown in Table II.

TABLE II
Performance comparison between basic and improved ant colony algorithm.

Ant colony algorithm	Optimal path length	Optimal iteration times	Average path length	Average iteration times	Average calculation time
Basic ant colony algorithm	28.63	14	28.69	35.8	11.04
Improved ant colony algorithm	28.63	5	28.69	5.75	8.23

The simulation results show that the basic and the improved ant colony algorithm have the same optimal route length and average path length, which shows that the basic ant colony algorithm can search the optimal path in a simple environment. The comparison of the convergence curve shows that the improved ant colony algorithm has a smoother convergence curve, while the basic ant colony algorithm has a more fluctuating convergence curve. At the same time, compared with the basic ant colony algorithm, the improved ant colony algorithm reduces the optimal number of iterations and the average number of iterations by 64.23% and 83.94%, respectively, indicating that the improved ant colony algorithm has relatively stable convergence and relatively fast convergence. The comparison of the average calculation time shows that the ratio of the improved ant colony algorithm is basically reduced by 24.45%, which indicates that the optimization rate of the improved ant colony algorithm is improved compared with the basic ant colony algorithm.

B. 30×30 environmental model

The above comparison shows that the efficiency of the improved ant colony algorithm in the simple environment is improved compared with the basic ant colony algorithm. To further verify the adaptability of the improved ant colony algorithm, the difficulty of increasing the environment from two aspects of environment space and obstacle complexity was selected. After running for 20 times, both the basic and the improved ant colony algorithm can get the optimal planning route, as shown in Fig. 6, and the respective corresponding optimal convergence curves are shown in Fig. 7 and Fig. 8, respectively.

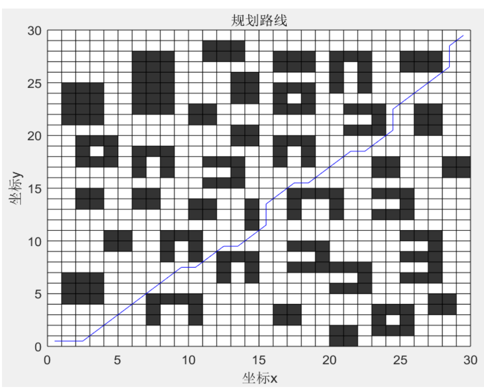

Fig. 6. Optimal route planning for two algorithms.

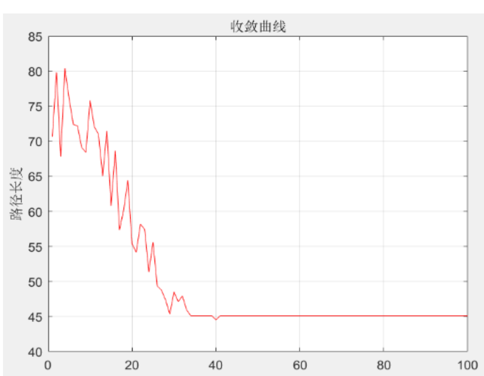

Fig. 7. Convergence curve of basic ant colony algorithm.

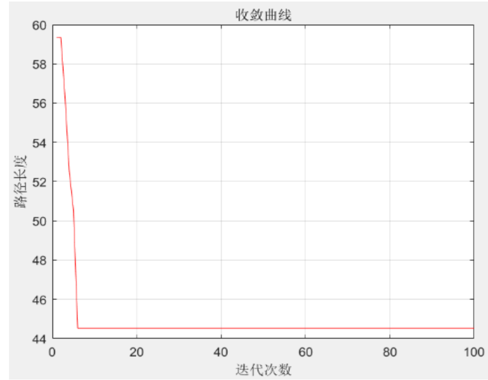

Fig. 8. Convergence curve of improved ant colony algorithm.

Like the statistical method in Table I, the statistical results under the 30×30 environment model are shown in Table III.

TABLE III
PERFORMANCE COMPARISON BETWEEN BASIC AND IMPROVED ANT COLONY ALGORITHM.

Ant colony algorithm	Optimal path length	Optimal iteration times	Average path length	Average iteration times	Average calculation time
Basic ant colony algorithm	44.53	41	45.77	51.75	40.83
Improved ant colony algorithm	44.53	6	44.64	8.45	29.48

The comparison between the optimal path length and the average path length shows that both the basic ant colony algorithm and the improved ant colony algorithm can find the optimal path, but the improved ant colony algorithm reduces the average path length by 2.47% compared with the basic ant colony algorithm, which indicates that the improved ant colony algorithm has a relatively stable ability to search for the optimal or better path length in a complex environment. The comparison of the convergence curve shows that although the convergence curve of the improved ant colony algorithm has a certain jitter, the basic ant colony algorithm not only has obvious jitter but also has a final trend value that is less smooth and stable than the improved ant colony algorithm. At the same time, compared with the basic ant colony algorithm, the improved ant colony algorithm reduces the optimal iteration times and the average iteration times by 85.37% and 83.67%, respectively, which shows that the improved ant colony algorithm has stable convergence and faster convergence speed. The comparison of calculation time shows that the calculation time of the improved ant colony algorithm is reduced by 27.80% compared with the basic ant colony algorithm, which indicates that the calculation speed of the improved ant colony algorithm is better than that of the basic ant colony algorithm.

According to the above comparison between simple environment and complex environment, the improved ant colony algorithm can maintain better advantages than the basic ant colony algorithm in terms of search length, computing power, and iteration times, and the improved ant colony algorithm can still maintain better performance advantages as the complexity of the environment increases.

VI. Conclusions

In this paper, an angle heuristic function is added to the state transition probability, and the method of differentiating pheromone update mode is used to improve the efficiency of the basic ant colony algorithm in planning the optimal route of a mobile robot. Simulation on the mobile robot environment model established by the grid method shows that the improved ant colony algorithm is superior to the basic ant colony algorithm not only in path searching ability but also in computing speed, especially in the convergence of the algorithm.

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